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Robust Adaptive Watermarking Based on Image Contents Using Wavelet Technique

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Abstract—A good watermarking scheme should be able to perform equally well on all types of images irrespective of image contents because practically watermarking has to be applied to images of all types. In this paper, it is shown that in wavelet based spread spectrum technique, watermarking at level 1 decomposition is better for textured images while watermarking at level 2 decomposition is better for non-textured images to achieve maximum robustness against various types of attacks. The proposed wavelet decomposition level selection algorithm utilizes the edge histogram to classify the host image as textured or non-textured image and automatically selects the level of decomposition for robust watermarking. The use of Spread Spectrum watermarking technique and Bior6.8 wavelet, results better robustness. Performance of the proposed scheme and its relative effectiveness is demonstrated on both categories of images under different attacks.

Index Terms—Wavelets, Bior6.8, Robustness, Correlation, Edge Histogram, Level of decomposition, Image Contents.

I. INTRODUCTION

The rapid advancement of internet and computer technology has facilitated authorized as well as unauthorized manipulation and reproduction of digital multimedia contents. Therefore, design and development of effective digital multimedia copyright protection methods to prevent unauthorized duplication or tampering have become necessary in present time. To this end, watermarking of digital content has evolved as a possible solution. An efficient and effective watermarking technique has to satisfy at-least three major requirements i.e. Imperceptibility, Robustness and sufficient Payload amount. Simultaneously maximizing all the three together is difficult as they are non-commensurable. Therefore, finding a solution that provides satisfactory values of these parameters is a challenging task. Several watermarking algorithms are reported in the literature. Initial efforts were in the spatial domains [1, 2, 3]. Later, several improvements of frequency domain watermarking [4, 5, 6] were reported. Among frequency domain techniques, wavelet based watermarking schemes are more attractive [7, 8, 9, 10, 11] due to several advantages such as space-frequency localization and multi-resolution offered by the wavelet transform. Image contents play a very important role in deciding the performance of the watermarking process. An image may have several regions having different types of contents such as smooth (low frequencies) or textured (high frequencies). Smooth areas have low distortion resistance while textured areas can bear higher level of distortion. In the literature, several techniques are proposed which utilize image contents for effective watermarking. A DCT based watermarking method based on image contents is given in [12]. This method proposes the creation of a Just Noticeable Distortion (JND) mask which contains the JND values of each pixel. The mask is prepared on the basis of some image features such as Texture, Edges and Luminance satisfying Human Visual Systems (HVS). This method uses spread spectrum technique but results regarding quality of watermarked images and watermark extraction under various attacks are not shown. A DFT based watermarking scheme based on image contents is presented in [13]. In this scheme host image is divided into 9 sub images in 3×3. Watermark is embedded only in those sub images which are highly textured to avoid noticeable artifacts. The textured image blocks are identified by the use of Harris Corner detector. The PSNR achieved is around 40dB. The quality of recovered watermark is not shown. Only the presence and absence of watermark is highlighted. A DCT based watermarking method is given in [14]. This method prepares a mask based on image features such as texture, luminance, corners and edges. It embeds the watermark in those areas, which are less sensitive to human eyes. It uses decimal sequences of watermarking instead of random sequence. The PSNR achieved is in range of 35 to 38dB and quality of recovered watermark is not mentioned. Another method of watermarking based on local image features is proposed in [15]. This method is based on computation of a Noise Visibility Function (NVF) that characterizes the local image properties with high texture and edge regions, where watermark can be embedded strongly without resulting visible artifacts. This method achieves PSNR in range of 25 to 34 dB while quality of recovered watermark is not discussed. A wavelet based watermarking method based on image contents such as texture and luminance is given in [16]. In this approach, masking is done pixel by pixel based on texture and luminance. PSNR achieved in this method is around 35dB for various images. Watermark detection is shown instead of watermark recovery. A watermarking algorithm based on image contents in Ridgelet domain is proposed in [17]. In this method, image is first partitioned into small pieces. These pieces are classified as weak texture or strong texture according to the statistical properties of columns coefficients in Ridgelet Transform (RT). The middle frequencies of RT sub-bands are selected and watermarks are embedded in the higher energy directions of the pieces with strong texture which are less sensitively to human's vision. Another content based watermarking in Fourier domain is given in [18]. In this scheme, a perceptual mask is generated, which identifies both textured as well as smooth areas of the images. The embedding strength is then adjusted according to the embedding areas. The weighted PSNR is computed as quality of embedding. A hybrid image watermarking scheme based on DWT and SVD is proposed in [19]. In this approach, the edge information of an image is used to embed the watermark. In addition, the particle swarm optimization algorithm is used to search the proper value of watermark embedding strength. Experimental work shows the robustness of proposed scheme against various image processing attacks. Another watermarking algorithm robust against geometric attacks, based on image features is proposed in [20]. In this scheme, Watermark is embedded in the areas represented by the salient features of the image. It is shown that in an image, Salient features are resistive to the geometrical attacks. These salient features also provide reference points used in watermark embedding and detection.

In all these methods proposed, the emphasis is on finding a suitable mask and adjusting the embedding strength of watermark accordingly. Most of the work is reported for the non-wavelet based techniques. Even in the case of few wavelet based schemes, the proposed content based methods do not explore the role and suitability of particular wavelet function, level of decomposition etc. in watermarking. Practically, whole image may belong to either smooth or textured category. How these proposed methods would deal with such cases, is not adequately discussed.

In this paper an attempt has been made to identify the image type first on the basis of its contents and then applying suitable wavelet based watermark embedding scheme. The rest of the paper is organized as follows. Section 2 provides motivation for the work. Section 3 describes the wavelet decomposition level selection algorithm. Section 4 explains the proposed watermark embedding and watermark extraction algorithms. Section 5 shows the experimental results and some conclusions are given in section 6 followed by the references.

II. MOTIVATION

It is well understood that textured images have more high frequency components at a given level of decomposition. Some higher order wavelets such as Db10, Bior6.8 etc. capture these high frequency details and produce larger wavelet coefficients as compared to smooth images. Due to large wavelet coefficients the embedding strength is not enough to maintain the impact of watermarking, which results poor watermark recovery. This is illustrated by using eight test images which are shown in figure 1. Four images of top row are smooth (non-textured) and rest four are textured. The textured images are taken from standard texture image database of Brodatz [21].

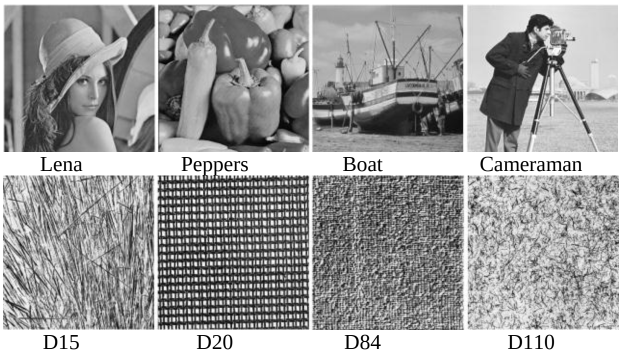


Fig 1. Textured and Non-Textured Test Images

The effect of image contents on robustness for textured and non-textured images is shown in table 1. The spread spectrum watermarkingis done on these images with embedding strength $k = 2$ and Bior6.8 wavelet. The watermark is embedded in diagonal wavelet coefficients (cD). The watermark embedding and extraction algorithms used in this process are explained in detail in section 4 of this paper. The energies of diagonal wavelet coefficients (embedding plane) at level-1 (EcD1) and at level-2 (EcD2) are also shown in table 1.The energies of diagonal coefficients show the amount of texture or randomness present in the image. Although sum of energies of all the detailed coefficients can also be considered for this purpose. The values of peak signal to noise ratio (PSNR) computed between original and watermarked images are shown in table 1. To show the quality of recovered watermark, Normalized Correlation Coefficient (NC) is computed between original and recovered watermark.

Table 1. Effect of Image contents on robustness

Images	Level 1		Level 2		Energy of cDs	
	PSNR	NC	PSNR	NC	EcD1	EcD2
Lena	30.71	1.00	37.53	1.00	6.73	109.33
Peppers	30.71	1.00	36.98	1.00	91.44	94.66
Boat	30.64	1.00	37.33	1.00	69.75	119.66
Cameraman	31.39	1.00	38.08	1.00	138.83	146.97
D15	31.20	1.00	37.99	0.94	107.44	1372.80
D20	31.37	1.00	37.98	0.98	116.14	660.53
D84	31.70	1.00	38.27	0.96	116.32	1279.70
D110	31.64	1.00	38.15	0.76	275.73	3167.70

It can be clearly observed from table 1, that large wavelet coefficients (higher coefficients energies) are obtained for textured images as compared to smooth images which dilute the embedding. Therefore, poor robustness as indicated by reduced values of NC at level 2, is obtained for textured images. There may be two approaches by which the robustness of watermarking can be maintained for textured images at par with smooth images.

Approach 1: The level of robustness can be increased by increasing the embedding strength for textured images while maintaining the level of decomposition ($L = 2$).
Approach 2: An alternative approach is to reduce the level of decomposition for textured images for watermarking while maintaining embedding strength ($k = 2$).

Both the approaches can maintain the desired level of robustness. Approach 2 is slightly better in terms of PSNR obtained. This can be seen as follows.

In approach 1, required higher embedding strength reduces the PSNR. While in approach 2, modifications in major frequency components at level-1 also reduce the PSNR. If the value of PSNR is maintained equal in both the approaches with adjustment of k, the value of NC will be slightly poorer in case of approach 1. At level-2 decomposition, the size of watermark embedding plane is smaller. This smaller size of coefficient matrix creates poor NC values as correlation is also affected by the size of data matrices. This slight reduction in NC of approach 1, can be overcome by further increase in embedding strength. But this will further reduce the PSNR. Therefore, to achieve same level of robustness, PSNR of approach 1 is slightly lower than that of approach 2.

Therefore, approach 2 is adopted for textured images. The degradation in PSNR for textured images is not a major issue. Due to large high frequency contents available in textured images, human eyes are not able to discern this degradation.

The discussion above concludes that non-textured images should be watermarked at level 2 while textured images should be watermarked at level 1 to achieve desired level of robustness for both types of images. This motivates a system which can identify the type of images (textured or non-textured) and watermark it accordingly. The level selection algorithm based on edge histogram is proposed in next section.

III. Level selection algorithm

In this section, approach 2 of previous section is described to maintain the desired level of robustness. The proposed level selection algorithm identifies the image type as to whether it is textured or non-textured and then applies either level-1 or level-2 watermarking accordingly. The scheme is outlined in figure 2.

To classify the images based on the contents, the Edge Histogram Descriptor (EHD) of Mpeg-7 [22] is suitably adapted. For classification, the whole image is divided into 16 non-overlapping blocks in 4×4 and each image block is then further divided into 2×2 pixel blocks as shown in figure 3.

From these 2×2 sub blocks, the local edge orientation is captured for the following cases: vertical, horizontal, diagonal45, diagonal135 and isotropic (non-orientation specific) types of orientations. These are shown in table 2 along with their detector operators.

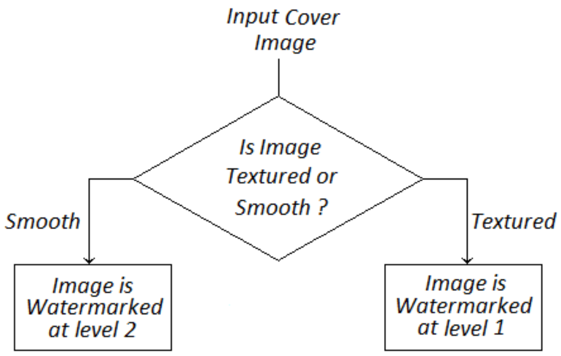


Fig 2. Adaptive Watermarking Algorithm based on image contents

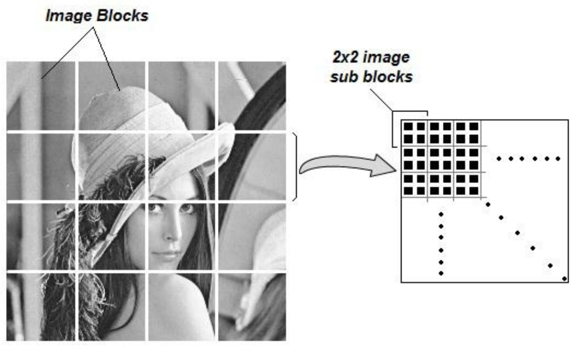
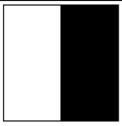
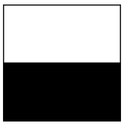
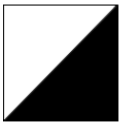
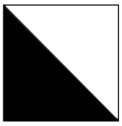


Fig 3. Image division for EHD calculation

The histogram for each sub-image represents the relative frequency of occurrence of the 5 types of edges in the corresponding sub-image. As a result, each local histogram contains 5 bins (Vertical, Horizontal, Diagonal45, Diagonal135 and Isotropic). Since there are 16 sub-images in the image, a total of $5 \times 16 = 80$ histogram bins are required to represent the image contents.

Table 2. Five types of local edge orientations and their detectors

Edge Type	Visual Representation	Operator Mask
Vertical Edge		$\begin{bmatrix}1 & -1\\ 1 & -1\end{bmatrix}$
Horizontal Edge		$\begin{bmatrix}1 & 1\\ -1 & -1\end{bmatrix}$
Diagonal (45^0)		$\begin{bmatrix}\sqrt{2} & 0\\ 0 & -\sqrt{2}\end{bmatrix}$
Diagonal (135^0)		$\begin{bmatrix}0 & \sqrt{2}\\ -\sqrt{2} & 0\end{bmatrix}$
Non-Orientation Type Edges		$\begin{bmatrix}2 & -2\\ -2 & 2\end{bmatrix}$

The edge orientation (EO) of a 2×2 sub block is captured by applying all five detectors as follows.

$$EO_{type} = \left| \sum_{k=0}^{3} a_k . d_k \right| \qquad (1)$$

Where, $[a_k] = \begin{bmatrix}a_0 & a_1\\ a_2 & a_3\end{bmatrix}$ represents 2×2 image sub block and $[d_k] = \begin{bmatrix}d_0 & d_1\\ d_2 & d_3\end{bmatrix}$, represents the edge detector. For one image block, by applying all these five operators on a 2×2 image sub block, the five values EO_v, EO_h, EO_{d45}, $EO_{d135}$and EO_{iso} are obtained and maximum of these five is compared with a threshold value (T_h) to find the dominant edge orientation as, $(EO_{dominant}) = max(EO_v,\ EO_h,\ EO_{d45},\ EO_{d135}, EO_{iso}) > T_h$.

The count of corresponding bin is increased by one and it is repeated for all 2×2 sub blocks. Thus a first image block out of total 16 is represented by 5 bins as $(b0, b1, b2, b3, b4)$. This process is repeated for all remaining 15 image blocks getting their 5 bins representation. For example, 2nd block representation is $(b5, b6, b7, b8, b9)$ and last block representation is $(b75, b76, b77, b78, b79)$. From this five value representation of all 16 image blocks, a matrix is prepared as shown in (2).

$$AllBins = \begin{bmatrix} b0 & b1 & b2 & b3 & b4\\ b5 & b6 & b7 & b8 & b9\\ . & . & . & . & .\\ . & . & . & . & .\\ b75 & b76 & b77 & b78 & b79 \end{bmatrix} \qquad (2)$$

The value of $GlobalBinAvg$ is computed by taking column wise and row wise mean of matrix $AllBins$ as,

$$GlobalBinAvg = mean\big(mean(AllBins)\big) \qquad (3)$$

In the proposed scheme, the value of $GlobalBinAvg$ is taken as decision level for finding whether an image is textured or non-textured. To validate the results of image classification algorithm based on image contents, several textured and non-textured images are taken for experiment. For this purpose, total 107 images of size 512×512 of both the categories are collected from various sources including standard image databases and Word Wide Web. The results of image separation on the basis of their $GlobalBinAvg$ are shown in table 3 and in figure 4.

In figure 4, the mean values of $GlobalBinAvg$ is also shown for both the categories of the images. Results shown in table 3 and figure 4 show the classifications of selected images on the basis of their edge histograms. There may be the possibility that some images lie on the verge of classification. This condition can lead to miss-classification of the images. But this is not the problem because in this scheme, the objective is not to implement the precise classification of images. The simple edge histogram based algorithm is sufficient to facilitate the proper watermarking of smooth and textured images to achieve better robustness.

Table 3. Results of Image classification based on image contents

Image Type	No. of Images	$GlobalBinAvg$ Min.	Max.	Avg.
Smooth (Low Frequency)	107	0.00	87.09	14.19
Textured (High Frequency)	107	122.18	643.15	300.59

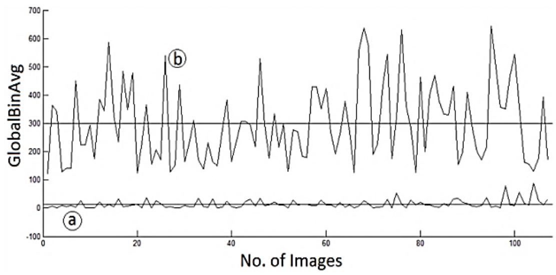


Fig 4. (a) $GlobalBinAvg$ profile of smooth images, (b) $GlobalBinAvg$profile of textured images

IV. Watermarking Scheme

The spread spectrum watermarking [6] is known to be robust against various types of attacks. In this paper, spread spectrum watermarking is used for watermark embedding and extraction for both types of images. Watermark embedding and extraction algorithms are explained in next subsections.

A. Watermark Embedding Algorithm

The steps of the proposed embedding algorithm are as follows.

Input: A grayscale image (I) of type uint8 and of size $M\times M$and a binary watermark (W).

Output: Watermarked Image (I_w).

1. The input image (I) is categorized into either textured or smooth image by the level selection algorithm described. If image is textured then decomposition level $N = 1$ otherwise $N = 2$ for smooth images.
2. Perform N-level wavelet decomposition of input image (I) to obtain four coefficients matrices cA_N, cH_N, cV_N and cD_N of size $\frac{M}{2^N} \times \frac{M}{2^N}$.
3. Select high frequency diagonal wavelet coefficient matrix cD_N for watermark embedding.
4. Select a seed to generate a Pseudo Random Sequence (PRS) of size equal to the size of frequency band cD_N and modify it to obtain matrix PN using the relation, $PN = R_1 \times (PRS - R_2)$, where, $R_1 = 2$ and $R_2 = 0.5$.
5. If watermark bit is 0 (Black) then modify the cD_N wavelet coefficients as, $cD'_N = cD_N + k.PN$, where, k isembedding strength. If watermark bit is 1 (white) then wavelet coefficients are left unchanged.
6. Repeat the step 4 and 5 for all '0' watermark bits with a newly generated PN sequence for each bit.
7. Take modified cD'_N to its original position and take inverse DWT to get watermarked image (I_w).
8. Compute the PSNR for I and I_w to determine the change in host image.

The embedding algorithm is shown in figure 5.

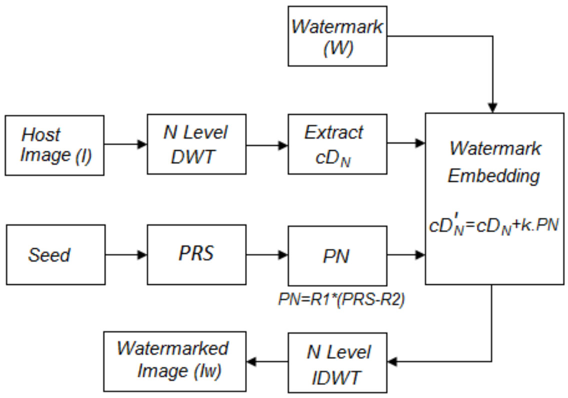


Fig 5. Watermark Embedding Algorithm for content based watermarking

B. Watermark Extraction Algorithm

Followings are the steps of watermark extraction,
Input: Watermarked Image (I_w) and Seed value.
Output: Extracted Watermark (W_R).

1. Decompose the watermarked image (I_w) in N levels and obtain the modified coefficients matrix cD'_N.
2. Generate the same random sequence (PRS), which was generated in embedding process using same seed value and convert the random sequence into $PN = R_1 \times (PRS - R_2)$ with $R_1 = 2$ and $R_2 = 0.5$.
3. Compute the correlation coefficients between random sequence (PN) and the modified coefficient matrix cD'_N as $r = corr2(PN, cD'_N)$. Repeat step 2 and 3 for all watermark bits and compute all correlation values r.
4. Compute the mean correlation value $(T = mean(r))$ and initialize a row matrix (W') having all values '1' equivalent to the size of the watermark.
5. For every watermark bit, compare r with T and modify the W' as follows,

$$W' = \begin{cases} 0, & r > T \\ 1, & otherwise \end{cases}$$

6. Reshape the row matrix W' into a matrix of size of original watermark matrix (W) to get recovered watermark (W_R).
7. Compute the NC between original watermark (W) and recovered watermark (W_R) to observe the quality of extracted watermark.

The watermark extraction algorithm is shown below graphically in figure 6.

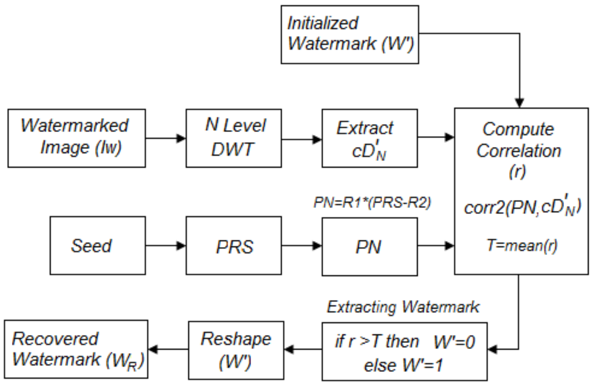


Fig 6. Watermark Extraction Algorithm for content based watermarking

V. EXPERIMENTAL RESULTS AND ANALYSIS

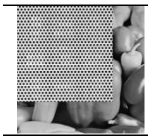
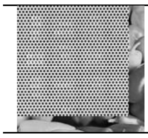
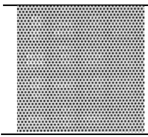
In this section, the proposed methodology is tested on various textured and non-textured images. These test images are already shown in figure 1. All test images are grayscale and of size 512×512. The binary watermark used is shown in figure 7.

Fig 7. Binary Watermark (21×12)

While computing $GlobalBinAvg$ of equation 3, the threshold value (T_h) is taken as 100. For the purpose of automatic wavelet decomposition level selection, the value of $GlobalBinAvg$ is chosen to be 120 as decision level.

This decision level will categorize the input host images as textured and non-textured images. The input images, those having $GlobalBinAvg$ below 120 will be categorized as smooth images, while those having $GlobalBinAvg$ above 120 will be considered as textured images. The decision level 120 is derived empirically by computing $GlobalBinAvg$ with amount of texture variation in input host image as shown in table 4.

Table 4. Watermarking evaluation with texture variation

Images	Level 1		Level 2		$Global\ Bin\ Avg$
	PSNR	NC	PSNR	NC	
Image: 512×512, Texture: 0×0 (0.00%)					
	30.48	1.00	37.04	1.00	29.53
Texture: 64×64 (1.53%)					
	31.71	1.00	38.20	1.00	34.05
Texture: 128×128 (6.25%)					
	31.76	1.00	38.47	1.00	47.18
Texture: 192×192 (14.06%)					
	31.79	1.00	38.47	1.00	69.00
Texture: 256×256 (25.00%)					
	31.90	1.00	38.47	1.00	100.18
Texture: 320×320 (39.06%)					
	31.90	1.00	38.54	0.9832	138.61
Texture: 384×384 (56.25%)					
	31.90	1.00	38.54	0.9750	185.94
Texture: 448×448 (76.56%)					
	31.90	1.00	38.54	0.9589	241.16
Texture: 512×512 (100.00%)					
	32.09	1.00	38.54	0.8530	302.68

All images in table 4 are watermarked with $k = 2$ using both level-1 and level-2 decomposition with Bior6.8 wavelet. This wavelet is chosen because Bior6.8 is a symmetric, biorthogonal wavelet with linear phase and gives better reconstruction with minimum error. The Peak Signal to Noise Ratio (PSNR) is calculated in dB between the watermarked image and original image. Normalized Correlation Coefficient (NC) between recovered watermark and original watermark is calculated under no attack condition.

From table 4, it can be observed that when the value of $GlobalBinAvg$ is 138.61 (39.06% texture), watermark recovery in level 2 is degraded with NC lesser than 1. Therefore, it is better to choose level 1 watermarking to improve watermark extraction.

Similarly when the value of $GlobalBinAvg$ is 100.18, level-2 watermarking performs well in watermark extraction. Thus, an intermediate value of 120 is chosen as decision level for automatic level selection for textured and non-textured images aiming at better watermark extraction. The analysis shown in table 4 is done for 512×512 image size. For an image half of its size, the decision level can be down scaled by 0.5 and similarly for image double of its size, it can be up scaled by 2 assuming that the amount of texture is proportional to the image size. It can be seen from table 4 that although decomposition at level 1 improves watermark recovery for textured images, the value of PSNR reduces. This is not a big problem as already discussed because due to more texture available in the image, this small degradation in image is almost imperceptible to the human eyes.

The performance of watermarking scheme along with level selection algorithm is tested under various attacks such as JPEG compression, Cropping, Noise addition, Filtering etc. and the results are shown in the tables 5 to 11.

The shaded areas in tables 5 to 11 show the preferred level watermarking for smooth and textured images depending on the value of GlobalBinAvg. The value of NC calculated between original and recovered watermark clearly shows that in all attacks the robustness is better for smooth images if they are watermarked at level 2 while it is better for textured images, if they are watermarked at level 1. The only exception is the case of blurring attack, where level 2 watermarking is more robust for textured images. This happens because, blurring attack removes high frequency details of the textured images, therefore, making them in the category of smooth images.

Table 5. Comparison of NC under JPEG Compression (Q=30)

Image	$Global\ BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	0.6112	37.53	0.9669
Pepper	29.53	30.71	0.8157	36.98	0.9916
Boat	30.64	30.64	0.7562	37.33	0.9916
Camera Man	84.74	31.39	0.8293	38.08	0.9832
D15	363.26	31.20	0.8686	37.99	0.8498
D20	260.71	31.37	0.9353	37.98	0.8868
D84	364.61	31.70	0.8960	38.27	0.8906
D110	402.08	31.64	0.8741	38.15	0.7529

Table 6. Comparison of NC under Salt & Pepper Attack (Strength=0.1)

Image	$Global$ $BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	1.0000	37.53	0.8835
Pepper	29.53	30.71	1.0000	36.98	0.8338
Boat	30.64	30.64	1.0000	37.33	0.8363
Camera Man	84.74	31.39	1.0000	38.08	0.8060
D15	363.26	31.20	0.9916	37.99	0.7433
D20	260.71	31.37	0.9916	37.98	0.8102
D84	364.61	31.70	1.0000	38.27	0.7992
D110	402.08	31.64	1.0000	38.15	0.6712

Table 7. Comparison of NC under Gaussian Noise Attack
($\mu = 0, \quad \sigma^2 = 0.003$)

Image	$Global$ $BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	1.0000	37.53	0.8800
Pepper	29.53	30.71	1.0000	36.98	0.9110
Boat	30.64	30.64	1.0000	37.33	0.9035
Camera Man	84.74	31.39	0.9916	38.08	0.9174
D15	363.26	31.20	1.0000	37.99	0.7628
D20	260.71	31.37	1.0000	37.98	0.8504
D84	364.61	31.70	1.0000	38.27	0.7963
D110	402.08	31.64	0.9916	38.15	0.6771

Table 8. Comparison of NC under Sharpening Attack
(Mask= [-1 -1 -1;-1 9 -1;-1 -1 -1])

Image	$Global$ $BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	1.0000	37.53	1.0000
Pepper	29.53	30.71	1.0000	36.98	1.0000
Boat	30.64	30.64	1.0000	37.33	1.0000
Camera Man	84.74	31.39	1.0000	38.08	1.0000
D15	363.26	31.20	1.0000	37.99	0.8624
D20	260.71	31.37	1.0000	37.98	0.9916
D84	364.61	31.70	1.0000	38.27	0.8979
D110	402.08	31.64	1.0000	38.15	0.7726

Table 9. Comparison of NC under Median Filtering Attack
(3×3 Mask)

Image	$Global$ $BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	0.9052	37.53	0.9833
Pepper	29.53	30.71	0.7760	36.98	0.9916
Boat	30.64	30.64	0.8007	37.33	0.9916
Camera Man	84.74	31.39	0.7760	38.08	1.0000
D15	363.26	31.20	0.9510	37.99	0.7430
D20	260.71	31.37	0.8979	37.98	0.7324
D84	364.61	31.70	0.8172	38.27	0.8221
D110	402.08	31.64	0.6411	38.15	0.6182

Table 10. Comparison of NC under Blurring Attack
(3×3 Averaging Mask)

Image	$Global$ $BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	0.6712	37.53	1.0000
Pepper	29.53	30.71	0.5994	36.98	1.0000
Boat	30.64	30.64	0.5398	37.33	1.0000
Camera Man	84.74	31.39	0.7004	38.08	1.0000
D15	363.26	31.20	0.6548	37.99	0.8741
D20	260.71	31.37	0.6258	37.98	0.9277
D84	364.61	31.70	0.5600	38.27	0.9201
D110	402.08	31.64	0.5046	38.15	0.6969

Table 11. Comparison of NC under Cropping Attack
(1/4th upper left is cut)

Image	$Global$ $BinAvg$	Level1		Level2	
		PSNR	NC	PSNR	NC
Lena	8.20	30.71	1.0000	37.53	1.0000
Pepper	29.53	30.71	1.0000	36.98	1.0000
Boat	30.64	30.64	1.0000	37.33	1.0000
Camera Man	84.74	31.39	1.0000	38.08	1.0000
D15	363.26	31.20	1.0000	37.99	0.8960
D20	260.71	31.37	1.0000	37.98	0.9832
D84	364.61	31.70	1.0000	38.27	0.9264
D110	402.08	31.64	1.0000	38.15	0.7298

VI. CONCLUSIONS

In this paper, an adaptive robust spread spectrum method of digital image watermarking in wavelet domain is proposed. The algorithm automatically selects the level of wavelet decomposition based on image contents to provide maximum robustness to both textured and non-textured images. The proposed scheme is tested for various types of images. The results show that there is good improvement in the quality (Correlation Coefficients) of recovered watermark under various attacks for textured images if they are watermarked at level 1. Though the watermarking at level 1 reduces the PSNR value of textured images slightly but better robustness is achieved. The small degradation in the value of PSNR for textured images is not a problem as due to more intensity variations in textured image, this small degradation of image quality is almost insensitive to human eyes. Similarly for smooth images, level 2 decomposition works well, where better robustness with high PSNR is achieved. High PSNR is necessary in case of smooth images to avoid any noticeable visual artefacts in the image.

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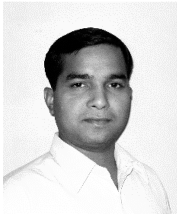
Authors' Profiles



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